MAPPING FUEL RISK AT THE LOS ALAMOS URBAN-WILDLAND INTERFACE

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ABSTRACT

Remote sensing and geographic information system (GIS) technologies support the goals of the Los Alamos region to use current technology in expanding information to reduce fire hazard within its wildland urban interface. The forests and woodlands on the east slopes of the Jemez Mountains are generally overstocked and carry the potential to produce intense wildfires that could threaten lives, property and natural resources. Overall overstory fuel classification accuracy was 96.10 %, with a kappa coefficient of .95. Average modeled understory fuel loads increase from 4.89 tons/acre in grass, to 28.29 tons/acre in ponderosa pine, 31.53 tons/acre in aspen, and 52.05 tons/acre in mixed conifer. The coefficient of variation, which measures the reliability of the means, is almost the same for the mixed conifer and ponderosa pine data, at around .34.
Keywords: fire risk, fuels, remote sensing, GIS

INTRODUCTION

The 1996 Dome Fire scorched over 16,000 acres and focused national attention on the need to protect the Los Alamos National Laboratory (LANL) and, more generally, the Los Alamos Urban-Wildland Interface (LAUWI). Map products depicting areas carrying high fuel loads and risk would reduce the vulnerability of LANL, associated LANL materials storage areas, resource values within Bandelier National Monument (BNM) and U. S. Forest Service (USFS) holdings, and would decrease wildfire threats to the townspeople of Los Alamos.

This paper reports first results of efforts to map and model overstory and understory fuel loads within the LAUWI. This project, underwritten by the Rocky Mountain Research Station, represents an investment of resources in support of its Urban Wildland Interface program. The LAUWI fuels risk map is based on the fire behavior fuel models identified in the National Fire Danger Rating System (NFDRS). Space-based remote sensor data, aerial photographic data, digital elevation models and ground surveys are being combined to produce the risk maps. Data from these maps can be input directly to fire growth simulators. Ground surveys are underway to establish and fine-tune map accuracies. Mapped fuel models are being reconciled with an accompanying digital terrain database, providing an inventory showing the topographic positions (elevation, slope and aspect) and total acreage of all NFDRS fuel classes. Following brief background covering motivations for this research and its legacy, we report data and methods used to produce the overstory and understory fuel risk products.

BACKGROUND AND MOTIVATION

The Los Alamos area is designated a Priority One Urban Interface Area in the Southwestern Region Urban Interface Planning Report, completed in summer 1997. The LAUWI was rated ‘high’ in risk, hazard, and value in the 1997 Santa Fe National Forest Wildfire Prevention Report. The LANL, BNM, USFS, Los Alamos and Santa Fe counties (Counties) together consider a fuels mapping and inventory project key to continued cooperative research, and important for establishing consistent methods and databases across administrative boundaries, in this case for collaborative fire management.

Fire threats to structures and people have motivated fire management in other regions. In Flagstaff Arizona, for example, the Flagstaff Fire Department is conducting prescribed burning inside city limits. With assistance from the Coconino National Forest, Americorps and Northern Arizona University, the Fire Department conducts prescribed burns aimed at reducing hazardous fuel thickets. Boulder County (Colorado) developed the Wildfire Hazard Identification & Mitigation System (WHIMS) to address wildfire hazards in the wildland urban interface. WHIMS combines expertise in hazard assessment, forest management, wildfire behavior and fire suppression with GIS technology, fire district and community involvement. The key to the success of WHIMS—and to the benefit of the project proposed here—is the direct contact, participation and educational experience of the Counties, LANL, BNM, and USFS. The LANL Interagency Wildfire Management Team (IWMT) currently coordinates acquisition and transfer of information to these groups, insuring the science underpinning the project is management-driven.

Remote sensing and GIS technologies support the goals of the LANL, Counties, BNM and the USFS to use current technology in expanding information to reduce fire hazard within the wildland urban interface. These technologies provide the analytical framework within which to map and model forest fuels using space-based remotely-sensed and topographic data. It is pointed out that remote forest fuel-load mapping remains experimental, but that management and economic payoffs of a successful fuel load mapping project may be substantial. The LANL is currently developing fire spread models, and is using mapped data produced from this project to test these models.

The forests and woodlands on the east slopes of the Jemez Mountains are generally overstocked and have the potential to produce intense wildfires that could threaten lives, property and natural resources. Although it is widely accepted that the forests and woodlands are dense and laden with fuels, spatial variations of the vegetational conditions and the topographic distributions of fuels remain uncertain. This uncertainty creates difficulties for facility managers and land managers who need to reduce the fuel levels and fire hazards but also need to spend their money wisely. A regional map displaying the geographic distributions of fuel levels and fire hazards thus assists managers in this decision-making process, promoting coordination among LANL and other land-management agencies in their implementation of fuels risk reduction activities.

DATA AND METHODS

Overstory Fuels Mapping

The data used during the mapping process are listed in Table 1. The ownership boundaries were used for display purposes only. The BNM fire effects monitoring data contain downed and woody data based upon standard sampling methods (Brown, et al. 1982). Downed woody material were identified by species in the BNM database, and were used to estimate the overstory forest type. All fuels sampling locations were located by differentially-corrected global positioning system (GPS) measurements.

Data Theme	Source
Landsat TM dated July 3, 1997; path 34, row 35	USGS EROS Data Center
1:24,000 Digital Elevation Models (DEM) Valle Toledo, Guaje Mountain, Puye, Bland, Frijoles, White Rock	USGS, Los Alamos National Laboratory (LANL) Facility for Information, Management, Analysis and Display (FIMAD)
Ownership Boundaries	Bandelier National Monument, LANL FIMAD
1:100,000 Roads, DLGs	USGS
BNM fire effects monitoring data	BNM
Valle Fuels Mapping data, 1997 and 1998	Valle Project
Valle Project Boundary	Digitized from hand drawn map created during Valle Project meeting May 14, 1998

Table 1.

Image Preprocessing

The DEM coverage obtained from LANL FIMAD adequately covers the study site, but some portions contained horizontal striping artifacts. Five of the six source DEMs were obtained from the USGS FTP download site. Original DEMs were required to de-stripe the DEMs: The Guaje Mountain and Valle Tolledo DEMs were processed with a multistage convolution filter to remove as much of the striping as possible (Crippen 1989). One of the six original DEMs (Frijoles) was not available from the USGS download FTP site, so these data were cut from the LANL dataset and merged with the other five datasets to obtain a seamless DEM for the study site.

The TM data were subset and georeferenced to an area covered by the six contiguous 1:24,000 DEMs covering the study area. Nineteen ground control points and a 2nd degree polynomial were used in the transformation to obtain a registration with an RMSE of .40 pixels. A Universal Transverse Mercator (UTM) projection with the North American Datum (NAD) for 1983 were used for the georeferenced data.

A dark object subtraction (DOS) algorithm was used to compensate the visible wavelength bands in the TM data for atmospheric scattering (Chavez 1988). Two cloud shadows over a canyon directly south of the Valle study site and the Abiquiu reservoir north of the study site were used to determine the number of digital numbers (DNs) to subtract. An iterative band ratio (IBR) technique was used to verify the number of DNs to subtract (Crippen 1989). The IBR protocol assumes a ratio of two bands will eliminate topographic effects in the absence of atmospheric scattering. The middle infrared band (TM7), is assumed to be free from atmospheric scattering. Subtracting DNs iteratively from the "noisy" band, then "ratioing" with band 7 until all topographic effects are eliminated from the "ratio" image effectively reduces scattering noise. Table 2 lists the number of DNs subtracted per band.

TM Band	Number of DNs subtracted
1	49
2	15
3	13
4, 5, 6, 7	0

Table 2.

The preprocessed data were "subset" to an area a little larger than the Valle Project study site to minimize further data processing time.

Maximum Likelihood Image Classification

Valle Project fuels data from 1997 and 1998 field campaigns (Balice et al., 1999), as well as the fire effects monitoring database from BNM, were used to train a maximum likelihood classifier. Data points from 1997 that were not within the Valle study site boundary were not used as training points. In addition, several points in Los Alamos Canyon were not used as training points due to registration errors even though the overall RMSE of the georeferencing was less than a pixel. (It is numerically very difficult to geometrically correct for steep topography even with a high order polynomial.). The BNM fire effects monitoring data do not directly classify the overstory canopy by forest type. When apparent that downed woody species plots represented overstory composition, these plots were qualified and used as training data. There is one sample location (AB0402) in the 1998 data that is in a Ponderosa Pine canopy at an elevation (2900m) where mixed conifer usually occurs. Because one site cannot define a training class, and this one site could not be distinguished from mixed conifer, it was eliminated from the training data.

Linear transformations of the six non-thermal TM bands were combined with elevation data and a texture image, producing a maximum-likelihood classification (Schowengerdt 1997). Linear transformations of spectral data typically compress spectral information and enhance statistical separability among classes. Elevation represents a multi-dimensional variable that mediates regional fuel type; thus elevation data were included to help resolve residual spectral confusion among classes. Texture represents spatial variations in pixel gray values, and can be used to discriminate regional types having distinctive spatial response patterns.

Two sets of linear transformations were produced: 1) brightness, greenness, and wetness features from the Kauth-Thomas coefficients (Kauth and Thomas 1976); and 2) the first two principal components from a non-standardized principal component analysis (PCA) (Schowengerdt 1997). The texture image was produced by convolving a 3x3 moving window with the visible red TM band, recording the range of gray levels within the processing window. The greater the range, the 'coarser' the apparent image texture (Anys, et al. 1998). Due to the low number of training sites for urban, grass, and aspen classes, adjoining pixels were added to training statistics, provided these statistics matched these sparse classes.

Overstory Fuel Mapping Results

Overall classification accuracy was 96.10 %, with a kappa coefficient of .95. The kappa coefficient, which ranges between 0 and 1, is a more conservative measure of the difference between the *actual* agreement between reference data and an automated classifier, and the *chance* agreement between the reference data and a random classifier (Congalton, et al. 1983). A kappa of 0.95 thus means that the classification accuracy was 95% greater than chance. The columns of Table 3 list the number of training sites per class. The rows detail how they were classified. Table 4 lists the resulting classification accuracy, and percentage of commission and omission errors per class. The number of pixels, acres, and hectares per class in the Valle study site appear in Table 5.

Understory Fuels Modeling

Data used to model the LAUWI understory fuel appear in Table 1. All data were transformed to the UTM coordinate system using GRS1980 as the spheroid and NAD83 as the datum. The BNM boundary from BNM coverage was used with the LANL and Los Alamos County boundaries from the LANL coverage to form the ownership boundary used for display purposes only. The Valle Project boundary was digitized from a hand drawn map and is meant to approximate the study site.

BNM fire effects monitoring data contain downed and woody fuels collected using standard sampling methods (Brown, et al. 1982). Downed woody fuels identified by species in the BNM database were used to estimate the overstory forest type. Sampled locations were located by differentially-corrected GPS measurements. All samples fall south of the Camp May road. Roadless areas south of the Camp May road are also unsampled. Individual understory fuel components measured at each site were summed to obtain a single understory fuel load value for the location. BNM fire effects data and Valle 1997 data falling outside the Valle project area were not used in this analysis.

The BNM and Valle 1997 data did not include fuel loads for shrubs and tree less than ten feet tall, in addition the BNM do not include herbaceous vegetation data. Duff loads from the Valle 1997 and 1998 data reported here are different than initially reported: All Valle duff loads were originally calculated using an average bulk density for southwestern Ponderosa pine of 4.9 lbs/ft^3 reported by Ffolliot et al. (1968). Duff loads reported here were computed with bulk densities used by BNM and are derived from later data collected by van Wagtendonk et al. (1998) in the Sierra Nevada. A bulk density of 10.45 lbs/ft^3 used for the mixed conifer is an average of the values from van Wagendonk for Douglas-fir and Western white pine. Bulk density for ponderosa pine is 9.64 lbs/ft^3.

GIS-Based Approach

This analysis estimated understory fuel loads using the topographic features of slope and aspect from a digital elevation model, and the overstory canopy type from the classification of a satellite image as determining variables of the understory fuels. Creating a surface from point data is a classic problem in spatial analysis. The objective here was to use understory fuel loads sampled at point locations to derive a surface repre-

Class	Urban	Grass	Mixed Conifer	Ponderosa Pine	Aspen	Total
Unclassified	0	0	0	0	0	0
Urban	6	0	0	0	0	6
Grass	0	2	0	0	0	2
Mixed Conifer	0	0	35	1	0	36
Ponderosa Pine	0	0	2	26	0	28
Aspen	0	0	0	0	5	5
Total	6	2	37	27	5	77

Table 3.

Class	Commission (%)	Omission (%)	Accuracy (%)
Urban	0.00	0.00	100.00
Grass	0.00	0.00	100.00
Mixed Conifer	2.70	5.41	94.60
Ponderosa Pine	7.41	3.70	96.30
Aspen	0.00	0.00	100.00

Table 4.

Class	Number of pixels	Percent	Hectares	Acres
Urban	17752	10.85%	1597.68	3947.87
Grass	9900	6.05%	891.00	2201.66
Mixed Conifer	98958	60.46%	8906.22	22007.27
Ponderosa Pine	34730	21.22%	3125.70	7723.60
Aspen	2335	1.43%	210.15	519.28
Total	163675	100.00%	14730.75	36399.68

Table 5.

senting the spatial distribution of surface fuels. The amounts of overstory and understory fuel are a function of moisture, as mediated by elevation, slope and aspect (Pyne 1996). In southwestern forests higher moisture levels are found on the north and east slopes and drier conditions occur on west and south slopes due to higher summertime insolation (Barton 1994). Forest overstory canopy type in the Jemez Mountains is predominately a function of available moisture. Moisture is typically associated the elevation, but canyons also support mesic conditions. Aspen and mixed conifer species occur at the higher elevations, ponderosa pine at the lower elevations. Variables derived from digital terrain models have been used in previous studies to predict vegetation patterns (Davis 1990). Franklin (1995) reviews predictive vegetation mapping using GIS techniques and environmental gradients. While this study is not predicting patterns of vegetation types per se, these techniques are applicable.

Three grid coverages of percent slope, aspect, and overstory canopy type were produced at 30m resolution as the basis for the model of understory fuels. Percent slope and aspect were derived from a 30m resolution digital elevation model. Slope data were grouped into five classes based upon the National Fire Danger Rating System (NFDRS, Deeming 1977). Aspect was divided into four classes representing the four cardinal directions. Overstory canopy classes consist of aspen, mixed conifer, ponderosa pine, grass, and urban. The overstory classification was derived from a Landsat Thematic Mapper image (Yool 1998). These three data layers were combined with a GIS union operation to create polygons of unique combinations of slope, aspect, and overstory class. Fuel load values at the field sampled locations having the same slope, aspect, and overstory canopy were averaged to obtain the fuel load value for that unique combination of slope, aspect, and overstory.

Understory Modeling Results

A summary of predicted understory fuel loads by overstory type is listed in Table 6. Average fuel loads increase from 4.89 tons/acre in grass, to 28.29 tons/acre in ponderosa pine, 31.53 tons/acre in aspen, and 52.05 tons/acre in mixed conifer. The maximum of 104.4 tons/acre in mixed conifer is larger than the next largest value by 16 tons/acre. The coefficient of variation, which measures the reliability of the means, is almost the same for the mixed conifer and ponderosa pine data, at around .34. The aspen class has the lowest coefficient of variation at a value of .2. The grass and aspen classes were, however, under-sampled with two and five samples, respectively.

Regional Type	Mean	Standard Error	Median	Standard Deviation	Sample Variance	Coefficient of Variation	Range	Min	Max	Count
Mixed Conifer	52.05	2.97	48.80	18.09	327.20	0.35	85.91	18.49	104.40	37
Ponderosa Pine	28.29	1.78	27.22	9.24	85.31	0.33	44.03	11.20	55.24	27
Grass	4.89	1.44	4.89	2.04	4.14	0.42	2.88	3.45	6.33	2
Aspen	31.53	2.88	29.71	6.45	41.58	0.20	15.79	25.97	41.76	5

Table 6.

Understory loads showed weak correlations to aspect and slope. Aspect correlated to understory load with an R = -.15 for all overstory classes. The mixed conifer understory load correlated to aspect with an R = -.36. Ponderosa pine data were sampled heavily in the east aspect, with 17 out of 27 samples, which biases the correlation. Understory fuels correlated to slope with an R = .24. One mixed conifer sample had a load greater than two standard deviations from the average at 104 tons/acre. If this sample is removed, the correlation to slope was R = .31. The correlation to aspect remained stable, with an R = -.36. Slope correlations may have been biased due to the samples skewed to the flatter slopes with 49 out of 71 samples in the 0-25.9% class, 18 samples in the 26-40.9% class, and only 4 samples in the 41-55.9% class.

CONCLUSIONS AND RECOMMENDATIONS

The LAUWI exhibits significant spatial variability in overstory and understory fuels. Such complexity challenges conventional strategies that use aerial photography and fieldwork. Yet it is important to meet the challenge of developing accurate fuel maps in the face of increasing fire risk and fire management mandates for this region. Initial findings, which we base on a modest number of samples collected in 1997 and 1998, show average fuel loads range from 4.89 tons/acre (grass), 28.29 tons/acre (ponderosa pine), 31.53 tons/acre (aspen), to 52.05 tons/acre (mixed conifer). The coefficient of variation, which measures the reliability of the means, is low and stable for mixed conifer and ponderosa pine fuels. Statistics for grass and aspen classes were, however, insignificant due to the small number of replicates.

Further collections should bring all statistics within the significant range, and supply a larger database to calibrate the spatial modeling. We recommend spatial modeling efforts be expanded to include, but not be restricted to, random function models. Exploratory design studies have begun in this area. We have identified, using principal component analysis, a multivariable composed of spatial and spectral variables that influence spatial variability in understory fuels. We intend to use geostatistical methods (i.e., kriging with external drift) to predict understory fuel loads from the sample point network. This kriged surface will depict expected values of understory fuels across the Valle project area. Results will be compared with the current understory map, based exclusively on cross-tabulating the sample point network with unique mixes of topography.

Where lives and property are at risk, it is appropriate to estimate the spatial variation in model errors. There is an alternative to expected values that is perhaps more consistent with the risk analysis framework of this project: Using a Monte Carlo protocol, stochastic conditional simulation predicts for each grid a statistical distribution of values. Map products produced from simulations incorporate real data values, and represent predicted values as a range and associated confidence interval. While such maps cannot be interpreted readily by fire spread simulators, the statistical behavior of the data could be very instructive, providing fire managers key information concerning the error structure/spatial accuracy of predicted understory fuel loads.

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